HHS Public Access
Author manuscript
Am J Prev Med. Author manuscript; available in PMC 2019 October 01.

Published in final edited form as:
Am J Prev Med. 2018 October ; 55(4): e81–e91. doi:10.1016/j.amepre.2018.06.012.

Advances and Controversies in Diet and Physical Activity Measurement in Youth

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Abstract

Technological advancements in the past decades have improved dietary intake and physical activity measurements. This report reviews current developments in dietary intake and physical activity assessment in youth. Dietary intake assessment has relied predominantly on self-report or image-based methods to measure key aspects of dietary intake (e.g., food types, portion size, eating occasion), which are prone to notable methodologic (e.g., recall bias) and logistic (e.g., participant and researcher burden) challenges. Although there have been improvements in automatic eating detection, artificial intelligence, and sensor-based technologies, participant input is often needed to verify food categories and portions. Current physical activity assessment methods, including self-report, direct observation, and wearable devices, provide researchers with reliable estimations for energy expenditure and bodily movement. Recent developments in algorithms that incorporate signals from multiple sensors and technology-augmented selfreporting

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This article is part of a theme issue entitled Innovative Tools for Assessing Diet and Physical Activity for Health Promotion, which is sponsored by the North American branch of the International Life Sciences Institute.

No financial disclosures were reported by the authors of this paper.

methods have shown preliminary efficacy in measuring specific types of activity patterns and relevant contextual information. However, challenges in detecting resistance (e.g., in resistance training, weight lifting), prolonged physical activity monitoring, and algorithm (non)equivalence remain to be addressed. In summary, although dietary intake assessment methods have yet to achieve the same validity and reliability as physical activity measurement, recent developments in wearable technologies in both arenas have the potential to improve current assessment methods.

INTRODUCTION

Dietary intake (DI), physical activity (PA), and sedentary behavior (SB) measurement among children have experienced significant changes in accuracy and precision afforded by emerging new technologies. Even though technologies for measuring PA and SB have been available for over a decade and achieved notable accuracy,[1] pediatric DI measurement methods have substantial error,[2, 3] and novel approaches to DI assessment continue to lack precision. Recent technological innovations in DI, PA, and SB measurement among children are the topic of this review. Although childhood is generally considered to involve individuals aged 2 through 18 years, what can be expected from the different technologies will vary by age of the child.

CURRENT METHODS TO ASSESS DIETARY INTAKE AND PHYSICAL ACTIVITY IN CHILDREN AND YOUTH

Alternative methods of DI, PA, and SB measurement are appropriate for different study designs, health purposes, and desired information. DI measures capture diverse elements (e.g., total caloric intake, specific nutrient intake, food groups, portion size, eating event, or bites taken). PA and SB measures also assess diverse elements (e.g., the type, duration, intensity, and sometimes location of PA and SB). Type typically consists of broad categorizations of PA and SB (e.g., ambulation, sleep) or specific types of activities or postures (e.g., walking, tennis, napping, cycling, or standing). Duration would ideally be measured throughout the entire 24-hour lifecycle[4] and across multiple days, weeks, or months, but usually that is not feasible. Intensity could be assessed in broad categories (e.g., moderate, vigorous) or as energy expenditure (EE) units over some period of time. Records (diaries), 24-hour recalls, and frequency questionnaires are the most commonly used self-reported assessment tools.[5,6] Self-report measures of DI, PA, and SB have significant accuracy (validity) and precision (reliability) limitations,[7,8] including recall or memory bias, participant burden, social desirability bias, and reactivity (i.e., the participant changes behavior to ease the burden or in light of the information).[9] Substantial bias (consistent underreporting) between self-reported energy intake and the gold standard of doubly labeled water (a measure of EE) have been demonstrated.[7] Although PA and SB assessment have progressed to more objective indicators of behavior (e.g., pedometers, accelerometers), these also have limitations. For example, wearable monitors worn on the hip do not detect upper body movement, or assess work (e.g., carrying weight), or posture (e.g., sitting versus standing). Sensors can be placed on specific parts of the body, such as on the thigh to detect posture,[10] but such special placement may increase participant burden, indicating a need for further innovative methods that minimize such constraints.

NEW DEVELOPMENTS IN BEHAVIOR MEASUREMENT IN CHILDREN AND YOUTH

Advances in DI, PA, and SB assessment have incorporated different forms of digital technology often in parallel, including: (1) computers in facilitating the self-report of behavior; (2) PDAs or smart phones for reporting and recording of behavior soon after it occurs (called Ecological Momentary Assessment [EMA]); (3) cameras in smartphones to take images primarily of foods (called "active" assessment because it requires initiation of the assessment and the use of image size markers, called fiduciary markers, by the participant); (4) wearable cameras that take images at short intervals (seconds) throughout the day (called "passive" assessment because no action needs to be taken other than putting it on and starting it at the beginning of the day); (5) various sensors, usually connected to some recording device; (6) integrated sensor and image methods; and (7) integrated sensor and behavior change intervention (Tables 1 and 2). Each technology is presented in sequence, first for DI and then for PA and SB combined.

Computers Facilitating Self-Report

Computer-assisted programs have been employed to improve the accuracy of the 24-hour dietary recall, including the Food Intake Recording Software System[11] and the Automated Self-Administered 24-Hour Recall (ASA24-Kids), adapted from the adult ASA24 system developed by the National Cancer Institute.[12] The ASA24 utilizes the Automated Multiple-Pass Method[13] to enhance accuracy and includes 20,000 or more images of foods, most in successively larger portions, to facilitate accuracy of portion size estimation.[14] To reduce participant burden, ASA24-Kids further eliminates elements, such as foods children do not commonly eat (e.g., quiche) and aspects of food preparation (e.g., added salt, fat content), most children cannot report.[15] Similar computerized systems have been developed for assessing children's DI globally (e.g., in Portugal,[16] Brazil,[17] and the United Kingdom[18]).

Although early procedures showed some improvement in categorizing foods[19,20] and portion size estimation,[21] methodologic challenges have also been reported. Comparison of recall data collected using Food Intake Recording Software System to criterion methods (e.g., direct observation) demonstrated a 35% intrusion rate (i.e., foods reported eaten, but were not) and a 15% omission rate (i.e., underreported foods eaten),[11] totaling to an approximately 50% food intake misidentification rate. Similar intrusion (27%) and omission (35%) rates were observed in studies that used ASA24-Kids, which were higher than a dietitian-administered recall (intrusions, 20%; omissions, 23%).[22] Inaccuracies in portion size reports have also been reported.[11] Unfortunately, ASA24-Kids is no longer available for general use on the National Cancer Institute website.

Ecological Momentary Assessment

EMA, an active real-time self-reported data collection technique that allows for flexibility in sampling time throughout the day, is thought to minimize errors of self-report because it minimizes the time between the occurrence of a behavior (e.g., DI, PA, and SB) and reporting of it. EMA facilitates multiple data entries per day, and sampling schemas can be random or based on reported or detected eating events (e.g., meals or snacks). When data entry was performed right after eating events, recall bias was minimized.[23] EMA enables examination of within-person variations in dietary behavior over time.[23,24]

Recent EMA efforts have used mobile technologies, including PDAs[25] and smartphone apps,[26,27] to record data. Despite prompts for data entry, which commonly range from two to seven per day in published studies,[25–27] compliance rates with EMA methods for dietary assessment over time have varied. The percentage of answered prompts per day in one 7-day study steadily decreased from 63% (day 1) to 23% (day 7),[27] whereas in another 7-day study, 71% of random prompts were completed.[20] EMA-assessed DI, compared with 24-hour dietary recalls, demonstrated concordance ranging from 66% to 90%, depending on food type.[26]

The physical and social contexts of PA are commonly assessed via EMA.[28] Prompting for self-report data when a person is engaged in activity in the natural environment improves ecological validity and reduces recall bias,[23] with moderately high participant compliance rates.[29]

Image-Based Active Assessment

Image-based active assessments capitalize on the camera function of contemporary mobile devices to minimize recall bias. Generally, image-based assessment methods require participants to follow specific picture-taking protocols. The resulting images are commonly processed either by trained dietitians or by automated processes. Automated image analysis driven by algorithms can require additional image capture protocols, which may affect data quality. For example, the Technology-Assisted Dietary Assessment system[30] requires an image to be taken with a fiducial marker, a visual indicator of size for automatic estimation of volume, of a meal at a 45° angle before and after the meal. Although preliminary evidence with adolescents[30] and toddlers[31] indicates ease of using systems like Technology-Assisted Dietary Assessment, other work indicates that complexity in image-taking protocols can impose participant burden that potentially leads to declines in image taking over time[30]

The active image-based approach to DI assessment is subject to underreporting[32–34] In addition to method limitations, technical challenges in automating image analysis have been documented. Furthermore, storage and "by hand" analysis of image data by trained personnel can accrue considerable error, researcher burden, and expense.[35] Nonetheless, although challenges remain with using image-based dietary assessment in isolation, images can be used as memory aids for self-reported dietary assessment[32,36] or dietary recall interviews.[33,37,38] Data captures through images may also be augmented by asking participants to insert text descriptors for captured images[39].

Image-Based Passive Assessment

With concerns for participant burden, several studies have focused on passive dietary assessment, which generally requires only putting and turning on the assessment instrument/sensor at the start of the assessment. The eButton[40] is one of the earliest passive dietary assessment devices and utilizes a camera among 11 other sensors in a relatively small circular device worn on the chest. The eButton takes front-facing (relative to the participant) images of whatever is in front of the child at frequent intervals (e.g., every 1–10 seconds) over extended periods of time (e.g., 12 hours) and encrypts and stores these images in built-in memory, along with other sensor-obtained data (e.g., accelerometer, light meter, etc.). At the end of each day, a procedure is initiated to upload the images for data storage and laboratory processing. Full-day images have been shown to improve 24-hour dietary recalls.[41] Substantial advancements in image analysis methods have been developed toward a completely automated system. Recent enhancements to the eButton include (1) automatic identification of dining plates of a known size,[42] thereby providing a basis for food portion size assessment[43,44]; (2) refined food shape and volume estimation with global contours[45]; and (3) improved estimation of volume of portions of different foods in the images guided by lines of the manually administered three-dimensional digital wire mesh.[46,47]

The eButton system has been tested in children both under laboratory conditions and at home and school.[48] Full-day passive video data from a wearable camera demonstrates substantially higher mean estimated caloric intake compared with a self-reported diet diary,[49] which is subject to systematic underreporting of caloric intake. However, personnel (dietitian) effort to review food-item images and need for additional data from participant interviews to identify foods not recognized by staff can be substantial.[48] Even though the time needed to analyze the images is high (i.e., approximately 9 hours for 1 day of images), access to the all-day images can provide mportant information regarding energy balance behaviors and their antecedents.[50,51]

Concerning the validity of the eButton's automated image detection of food, an artificial intelligence procedure attained accuracy of 91.5% in the initial sample, and 86.4% in the cross-validation sample of images.[52] For food identification, dietitians attained 77.0% agreement with child/parent reporting of intake after seeing the images.[53] Under semi-laboratory conditions, mean relative error using a three-dimensional wire mesh procedure for estimating portion size was 2.8%.[46] Against manipulated food portion sizes, two dietitians using this three-dimensional wire mesh procedure attained intraclass correlation validity coefficients of 0.766 for volume served, 0.596 for volume left after intake and 0.677 for intake volume, but the engineers who helped create the wire mesh system did substantially better.[47] Two dietitians attained intraclass correlations of 0.65 with child/parent reported portion size estimation after seeing the images.[53] Thus, validity coefficients were better under laboratory circumstances, when fewer foods were involved; dietitians did not do as well as the engineers who helped create the system (suggesting additional training was necessary to enhance competence); and validity coefficients were not as high as might be desired for immediate use as an off-the-shelf system. Continuing research to automate all components holds the promise of enhancing accuracy and ease of use of this system.

Wearable, front-facing cameras now permit in-field passive direct observation of PA,[54] including categorizing types of PA,[55] and assessing the environment of active transport.[56] Researcher burden, however, has limited implementation, which awaits further advances in digital processing of the images for PA variables.[57]

Sensor-Based Methods

Wearable sensors enable identification of key indicators of eating behavior (e.g., chews, swallows).[58] Sensor data to date have only been collected in adults (outside of the eButton), but nothing inherently precludes use of these technologies with children. Signals from a combined sound sensor over the laryngopharynx and a bone conduction microphone to assess swallowing, and a below-the-ear sensor to detect chewing, demonstrated greater than 90% accuracy in detecting periods of food intake (within a resolution of 30 seconds). Artificial intelligence algorithms were trained to differentiate solid foods from liquids, and predict mass of solid foods consumed.[59] Combining sensor data with videos, the sound sensor data further provided accurate prediction of energy intake.[60,61] Others have combined motion sensors and physiologic electric signal detectors to detect eating events.[62,63] High accuracy in detecting eating events has also been reported using an electroglottograph for detecting electrical impedance across the larynx by the passing of food during swallowing.[64]

A transcutaneous sensor using resonance Raman spectroscopy has been developed and used to measure carotenoid status, an indicator of fruit and vegetable intake.[65,66] Considered a biomarker, this method measures skin carotenoid status that reflects intake over multiple weeks, but is confounded by smoking and adiposity. This is a promising method for those primarily interested in fruit and vegetable intake.

Miniaturized sensing devices enable passively measuring aspects of PA[67] and SB.[68] Measurable aspects of activity are in three categories: bodily movements (e.g., walking, running), the physiologic or cardiovascular indicators of the physical exertion or SB, and the context in which behaviors take place (including past and anticipated behaviors and information about the current environment).

Accelerometers have been used to assess PA in children and adolescents for more than 20 years.[69,70] Because of the affordability and practicality of accelerometer-based objective sensing, it has become standard even in large-scale studies, such as the U.S. National Health and Nutrition Examination Survey[71] and the U.K. Biobank studies.[72] These microelectromechanical system accelerometers measure acceleration, which can be used to assess overall motion of a part of the body.[73] When the devices are worn on the waist or hip, they can measure large-scale body movements that correspond to activity, such as ambulation. Gross measurement of movement can be scaled based on age and used as a proxy for activity intensity categorization or EE estimation.[74] Initially, accelerometers had insufficient battery and memory capacity to store the "raw" accelerometer data, instead using microprocessors to compute and store motion summary values, called "counts." Sometimes counts were collected from a single axis of accelerometer data, and typically values represented 1 minute of activity. Such data were then processed with age-specific "outpoint" algorithms to infer EE. Although the doubly labeled water method is considered the criterion for EE, accelerometers offer researchers a noninvasive and objective alternative for estimating EE.[75] Augmenting accelerometer data with physiologic information (e.g., heart rate) can lead to improved EE estimates.[76]

Recently, electronics have improved so that an inconspicuous monitor can collect and store raw triaxial accelerometer signals at a sampling rate of more than 60 times a second and run for multiple weeks on a single charge. Simple cutpoints in distributions of accelerometer readings do not capture all the information about PA and SB in these data. Some PA and SB researchers now propose abandoning cutpoint algorithms for new methods that exploit the information present in the raw signal.[77] Such methods can use features in the raw data stream to not only improve EE estimates,[78] but also to measure other aspects of PA, SB, and sleep, detecting specific types of activity.[79,80] Moreover, using pattern recognition algorithms with raw data can differentiate wrist gesturing from true ambulation,[72,81] which has led researchers to move the sensors from the hip to the wrist, so as to capture both PA, SB, and sleep behavior, with high rates of wearing the instrument.[82] Researchers are now able to study the 24-hour activity cycle, and the relationship between not only movement and health, but the specific reasons or ways that people are moving their bodies. Physiologic monitoring, in addition to motion-based monitoring, is also being used to study the activity of youth.[83–85] Practical options for measuring physiology related to PA while someone is outside of the laboratory setting include heart rate, galvanic skin response, and skin temperature sensors. Nonetheless, the burden of wearing physiologic sensing devices, especially those that provide the most reliable data with stick-on attachments, has limited widespread use for multisensor measurement of PA, SB, and sleep.

New research-grade activity monitors have shown improved ability to detect bodily movement via algorithms developed using limb-worn accelerometers (e.g., wrist and ankle[81]). Some newer versions of accelerometer-based activity monitors are augmented with additional sensors to improve detection of posture (e.g., inclinometer[86]), orientation (e.g., gyroscope), and also some contextual information (e.g., light sensor[87]).

Passive mobile sensing, such as GPS devices or location sensors in mobile phones, can be used to identify and characterize the physical environments in which youth engage in PA (e.g., outdoor play time[88,89]) and to aid identification of PA patterns that are challenging to assess using an accelerometer alone (e.g., independent mobility,[88] travel distance and speed,[85,90] and active transportation[91]). In-environment sensing, using special-purpose devices that i factors of interest, such as air quality,[92,93] can provide additional context about the environment in which they do it. For example, in-home or in-school sensors could provide cues about what type of activity children are engaged in or additional information about their sleep patterns.[94,95]

Integrated Sensor and Image Methods

Current advances in dietary assessment technologies largely target data processing by applying artificial intelligence software to sensor signals, sometimes also with images, for detecting or discriminating events, bouts, or types of behavior. For example, to minimize the numbers of images needed to be reviewed to estimate portion sizes, the study by Sazonov et al.[96] used data from wearable sensors to mark images for review only when the sensors detected eating. The accuracy of this combination of sensors and images in identifying foods and quantifying portions has not yet been reported. Because complex foods come in combinations in the same dish (e.g., stews, pizza, sandwiches, fried rice), another integrated method, DietCam, employed an initial ingredient detector, then machine learning algorithms with a texture detector, followed by machine learning algorithms for food clarification, which achieved greater than 85% precision across food groups of different complexity.[97] These advances require artificial intelligence software, which has become a major focus of innovation in diet assessment.[98]

Integrating Digital Measurement With Behavior Change Interventions

A fully integrative sensor approach for measuring and changing behavior is the Monitoring and Modeling Family Eating Dynamics[99] system, which incorporates several sensors and devices (including smartwatches, mobile devices, and beacons) to passively detect eating events and intervene in real time to encourage dietary change. Monitoring and Modeling Family Eating Dynamics focuses on the home food environment for all family members, including children. Accelerometers and gyroscopes on smartwatches automatically detect eating events, an approach to eating detection that was previously used exclusively in adult populations.[100–102] EMA surveys administered via smartphones collect data on context, including reasons for eating and who is eating with the user. This cyberphysical system is currently under development.

Sensor-based systems have been used to provide just-in-time feedback to promote or repress particular eating behaviors. One example used a piezoelectric strain sensor placed on the temporalis muscle, attached to the stem of an eyeglass frame, which was combined with an accelerometer to attain a 99% accuracy rate in differentiating eating from PA events,[103] common speech, and motion artifacts.[104] This system monitored chew counts and provided just-in-time feedback (i.e., during the eating event) to participants. Just-in-time feedback targeting a 25% reduction in chew counts resulted in a reduction in food mass and energy intake.[105] The AutoDietary system captures the Bluetooth-linked acoustic data acquired by a throat-worn unit, then processes the data on a smartphone in real time, and provides feedback to wearers on chewing frequency, snacking, and specific foods consumed.[106]

Smartphones and other commercially available wearable devices are equipped with a host of sensors (e.g., accelerometer, location, or gyroscope) that are increasingly being used to assess youths' PA and SB, as well as vehicles to provide behavior change interventions.[29,107,108] Smartphone data can detect key activities that contribute to EE (e.g., examples from the adult literature include sitting, standing, walking, and jogging[109]), although more work remains to be done to reliably detect these activities regardless of how phones are used and carried. Phones using context-sensitive EMA[110] can gather contextual information about youth PA, process that information in real time, and use the results to generate context-sensitive prompts in response to relevant contextual information (e.g., type of (in)activity, social and physical context, and lack of data).[111]

CHALLENGES IN DIETARY INTAKE AND PHYSICAL ACTIVITY MEASUREMENT IN CHILDREN

Although both active imaging and EMA dietary assessment methods, and accelerometer measures of PA, have been commonly used, a number of challenges still face most of the other innovative technological methods. Passively recorded camera images have intuitive appeal for identifying types and amounts of foods consumed, but enthusiasm has been tempered by the early inability to automatically identify the foods and the substantial amount of time to manually process food images. Conversely, recent efforts to automatically detect eating events and to limit the number of images taken and in turn, minimize the time necessary to process the smaller number of images hold promise to advance the field. Advances in artificial intelligence software for identifying images with foods (from a stream of images), as well as to identify specific foods in those images, also offers the promise of further limiting the time necessary to process images. For the foreseeable future, however, interviews with the participating users will likely be needed to verify the foods and portions that were automatically or manually identified, and to identify foods and portions when the camera may have been turned off or images are blurred or too dark. Rapid progress in many aspects of the relevant technologies is minimizing these limitations.

Although advancements in sensor technology and algorithm development have improved abilities to measure PA, SB, and EE, challenges remain (e.g., measuring movement with resistance during resistance training and weight lifting); measuring behavior and context for long periods of time, affordably, without burdening participants; and algorithm (non)equivalence using outpoints (i.e., activity intensity estimates differ based on algorithm selection, which hinders comparability of accelerometer-based PA measurements across studies).[112] For example, in a recent study using data from the International Children's Accelerometer Database, estimated daily minutes of moderate to vigorous PA ranged from 29.7 to 126.1 minutes, depending on the algorithm used.[112] The use of increasingly sophisticated algorithms, processing increasingly heterogeneous sensing data, gathered by a diverse set of devices that are rapidly changing, creates a data harmonization challenge. This challenge can only be addressed with transdisciplinary, collaborative efforts to collect and label sensor data for algorithm development and verification. One such project, the Repository for Algorithm Development in Ambulatory Research led by the National Cancer Institute, focused on the development of shared ontologies across disciplines (i.e., a common vocabulary and set of interrelationships among terms to permit pooling what was learned from different studies)[113] to improve and foster promising future sensor-driven approaches for richly measuring activity in adults and children.

CONCLUSIONS

There has long been recognition of the relevance of DI, PA, and SB behaviors to clinical health outcomes across all populations. Although many health practitioners discuss these behaviors with patients, the discussion can be limited and nonspecific because of the self-reported and thus biased nature of current clinical measures of dietary and PA behaviors. Although DI assessment methods have yet to achieve the validity and reliability now available for technology-enhanced PA measurement, the development of wearable technologies in both arenas opens the possibility for valid capture of real-time health behavior performance in a given patient. Availability of such data will provide new opportunities for personalized behavioral intervention and feedback that incorporates effective behavioral change strategies.

Choosing measurement technologies is complex and depends, in part, upon the populations and the settings where they will be deployed, the research questions being addressed, and of course the fast-paced improvement of existing—and development of new technologies. It is beyond the scope of this paper to aid the reader in specific choices. Rather, the main contribution of this paper is to point the reader toward emerging technologies for diet and PA assessment in youth. As the field moves forward, it is important to consider that the development of mobile and connected tools to assess diet and activity is inherently a transdisciplinary task and requires collaboration across disciplines such as (but not limited to) engineers, computer scientists, nutritionists, exercise scientists, behavioral scientists, and medical experts. The field will move forward much more rapidly if researchers commit to using open software architectures that facilitate sharing of code and algorithms and building upon existing work rather than forcing each research group to reinvent the wheel. Many of these methods are still under development and not yet available for general use. In conclusion, technological tools are becoming available that will enable diet and PA health interventions to meaningfully improve health outcomes.

ACKNOWLEDGMENTS

This review was inspired by discussions at a 2016 expert forum ("Tech Summit: Innovative Tools for Assessing Diet and Physical Activity for Health Promotion"), which was organized by the International Life Sciences Institute (ILSI) North America with the help of scientists from the University of California, San Diego (UCSD), the U.S. Department of Agriculture Agricultural Research Service, the American College of Sports Medicine (ACSM), and NIH. In-kind support was received from UCSD and financial contributions were provided by ACSM and the ILSI North America Committee on Balancing Food and Activity for Health. Additional funding from the ILSI North America Committee on Balancing Food and Activity for Health was allocated for the preparation and publication of papers following the forum. ILSI North America is a public non-profit foundation that provides a forum to advance understanding of scientific issues related to the nutritional quality and safety of the food supply by sponsoring research programs, educational seminars and workshops, and publications. ILSI North America receives support primarily from its industry membership. The opinions expressed herein are those of the authors and do not necessarily represent the views of the funding organization. Donna Spruijt-Metz received an honorarium from ILSI North America and is also supported by grants from the National Science Foundation (NSF-SCH 1521740) and NIH (R01AT008330). Cheng K. Fred Wen is supported by a University of Southern California PhD fellowship and a grant from NIH (ROI AT008330). Brooke M. Bell is supported by a grant from the National Science Foundation (NSF-SCH 1521740). Tom Baranowski received institutional support from the U.S. Department of Agriculture, Agricultural Research Service (Cooperative Agreement 58–3092-5–001). This article has been reviewed and approved for submission to the *American Journal of Preventive Medicine* by ILSI North America. ILSI North America had no role in the study design; collection, analysis, and interpretation of data; writing the report; and the decision to submit the report for publication.

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Table 1.

Summary of Dietary Intake Assessment Technological Tools in the Field

Outcome measure/Technology	Main feature	Limitations	References
Type and portion of food intake			
Automated 24-hour recall (ASA24-Kids)	Uses colorful drawn images of the foods to prompt accurate food recall	Self-report error; intrusions and omissions were higher when the child completed the ASA24-Kids alone than a dietitian-administered recall	12, 14, 15
Image-based active assessment	Participants take pictures of their food, and then trained dieticians automated processes that process the images	Image quality problems; high participant burden; difficulty with automating image analysis	30, 32–34
Type and frequency of food intake			
EMA	Collection of dietary intake data at or near the moment when an eating event occurs via a mobile device survey; data collection can be based on eating events, randomly sampled times, or another appropriate sampling scheme; dietary intake data are retrieved at multiple time points	Decreased compliance and attrition rates due to participant fatigue	25–27
Portion and/or frequency of food intake			
Wearable sensors	Capable of collecting data in frequent intervals; can be used to monitor eating events and provide just-in-time feedback; high accuracy in detecting periods of food intake, especially when sensors are combined	Sensors may interfere with daily activities (e.g., sports); sensors can malfunction; very time-consuming process for dieticians to visually identify the portions for most foods	48, 57, 60, 62, 94, 101, 104

ASA24-Kids, Automated SellA Administered 24-Hour Recall adanted for children; EMA, ecolosical momentary assessment.

Table 2.

Summary of PA Assessment Technological Tools in the Field

Outcome measure/ Technology	Main feature	Limitations	References
Context of PA			
EMA	Flexible prompting frequency; implementable with smartphones or text messages; provide improved ecological validity and reduced recall bias compared to paper diary	Self-report data; potential for recall bias; possible missing data due to participant noncompliance	28
GPS	Sensed location for context-sensitive EMA	Potential participant burden with having multiple devices	108, 109
Bodily movement			
Accelerometers	Validated in children and youth; can be worn on various body locations (waist, wrist, and ankle); additional sensors that help improve detection of posture (e.g., inclinometer), orientation (e.g., gyroscope), and also some contextual information (e.g., light sensor)	Expense; inability to provide contextual information; challenge in comparing accelerometry data across different protocols; limitation in detecting some strenuous activities (e.g., weight training)	
Specific types of activities			
GPS	Passive mobile sensing; ability to identify PA patterns that are challenging to assess using accelerometer alone (e.g., independent mobility, travel distance and speed, and active transportation)	Potential participant burden with having multiple devices	83, 86, 88, 89
EE			
Accelerometer	Validated in children and youth	Limitation in estimating EE in some types of exercise (e.g., cycling)	
Heart rate monitor	Provide improved EE estimate when using with accelerometer	Potential participant burden with having multiple devices	81–83

EE, energy expenditure; EMA, ecological momentary assessment; PA, physical activity.